Region One
Vegetation Classification, Mapping, Inventory and Analysis Report

Numbered Report NRGG 15-02 **February, 2015**

Nez Perce-Clearwater National Forests (NPC) VMap Version 14 Methodology

Robert S. Ahl, PhD
Stephen R. Brown Jr.
USDA Forest Service, Region 1
Engineering Staff
200 E. Broadway, Missoula, MT 59802

1. DATA

Image Data

The two cost effective data sets available for interpretation and mapping are Landsat Thematic Mapper (TM) and National Agriculture Imagery Program (NAIP) imagery. Both of these datasets have properties that add value to mapping work, and are available at no additional cost to the public.

The Landsat constellation of satellites has been in orbit since 1972 and has a long history of use in vegetation mapping and monitoring. The TM is considered a moderate resolution sensor, with 30 meter pixels, but it has high radiometric resolution allowing for increased discrimination between vegetation types. The footprint of a Landsat scene covers nearly 100 square miles, thereby making it effective for landscape-level mapping because it provides consistent spectral values over large areas.

Imagery provided by NAIP yields a higher spatial resolution, using 1 meter pixels, yet lacks some of the radiometric characteristics provided by TM data. The NAIP imagery consists of just 4 bands of data, spanning the visible spectrum into the near-infrared (NIR). The main drawback of this imagery is that each image tile covers approximately 30 square miles and therefore radiometric readings can be less consistent across large landscapes. The polygon-based map units delineated from these data are very accurate as compared to what can be accomplished from Landsat alone, and the secondary statistics derived from NAIP are useful for detailed delineation of various cover types.

In short, both Landsat TM, and NAIP imagery have useful properties for interpretation and mapping purposes. Landsat provides consistent and refined spectral values over large areas, and NAIP provides high spatial resolution for delineation, texture analysis, and visual interpretation. When used in combination these two image products complement each other very well, and provided the foundation for the production of the NPC VMap V14 Database. Below is a brief description of the image products used in this project.

- Landsat Thematic Mapper imagery: A mid-summer 2011 image was selected to capture “peak greenness” vegetation prior to senescence. Landsat TM images are distributed with 30 meter pixel resolution and seven bands of spectral information. We used bands 1, 2, 3, 4, 5, and 7 in this project. All TM images were orthorectified to the color infrared NAIP imagery, and radiance/reflectance corrected. The 30 meter pixel product was ultimately resampled to 10 meters and used in combination with NAIP data for quantitative analysis.

- National Agriculture Imagery Program data: NAIP imagery used in this project was also collected in 2011, and is provided with four spectral bands including the blue, green, red and near infrared (NIR) components. The original digital images were delivered with a 1 meter ground sample distance (GSD) and rectified to National Mapping Standards at the 1:24,000 scale. This imagery was used in two distinct ways: 1) the original 1 meter resolution data were used for visual inspection and interpretation in the mapping process, 2) the high resolution data were resampled to 10 meter pixels and used with TM data for quantitative analysis.

Image Derivatives and Ancillary Data

In addition to the values provided by the raw imagery, a variety of image derivatives and vegetation indices were computed from both datasets. The combination of the two image sources provides abundant spectral and texture-based information that is very useful for landcover mapping.

Image derivatives computed from the TM data include: a tasseled cap (TC) transformation, the first three principal components (PCA) of the TM data, and the first three principal components calculated on the TC transformation.

Derivatives of the NAIP imagery include: calculation of a normalized difference vegetation index (NDVI), quantification of intensity-hue-saturation (IHS), and the extraction of the first three principal components of the four band data. In addition to these spectral interpretations, two measures of image texture were computed for the four band NAIP image with a 5x5 pixel window. The first measure of texture accounts for the mean standard deviation within the analysis window, while the second measure records the minimum standard deviation within the analysis window. The mean texture is useful for delineating edges of patches and the minimum texture is useful for discriminating differences within patches. Texture derivatives are generally useful for interpretations of roughness related to vegetation types, canopy cover, and tree size estimates.

Ancillary datasets used to describe biophysical setting are also incorporated to better model the type, structure, distribution, and abundance of vegetation across the landscape. A 10 meter resolution digital elevation model (DEM), obtained from the National Elevation Dataset (NED) was used to characterize and quantify topography, and produce a variety of topographic derivatives that provide biophysical interpretations.

All of the direct and derived classification variables used in the production of NPC VMap V14 Database, are listed in Table 1. The various image, image derivatives, and topographically based products are used throughout the VMap production process.

Table 1. *Image and topographic variables used to derive the NPC VMap, V14 Database*

Image Input	Image Description
MEANIHSC1	NAIP CIR intensity
MEANIHSC2	NAIP CIR hue
MEANIHSC3	NAIP CIR saturation
MEANIHSR1	NAIP RGB intensity
MEANIHSR2	NAIP RGB hue
MEANIHSR3	NIAP RGB saturation
MEANCNDVI	NAIP CIR normalized difference vegetation index
MEANCPCA1	NAIP CIR 1st principal component
MEANCPCA2	NAIP CIR 2nd principal component
MEANCPCA3	NAIP CIR 3rd principal component
MEANNAIP1	NAIP band 1: red
MEANNAIP2	NAIP band 2: green
MEANNAIP3	NAIP band 3: blue
MEANNAIP4	NAIP band 4: near infrared
MEANTM1	LANDSAT TM band 1: blue
MEANTM2	LANDSAT TM band 2: green
MEANTM3	LANDSAT TM band 3: red
MEANTM4	LANDSAT TM band 4: near infrared
MEANTM5	LANDSAT TM band 5: mid infrared
MEANTM6	LANDSAT TM band 7: mid infrared
MEANTNDVI	LANDSAT TM normalized difference vegetation index
MEANTPCA1	LANDSAT TM 1st principal component
MEANTPCA2	LANDSAT TM 2nd principal component
MEANTPCA3	LANDSAT TM 3rd principal component
MEANTC1	LANDSAT TM tassled cap transformation: brightness
MEANTC2	LANDSAT TM tassled cap transformation: greenness
MEANTC3	LANDSAT TM tassled cap transformation: wetness
MEANTCP1	LANDSAT TM 1st principal component of the tassled cap transformation
MEANTCP2	LANDSAT TM 2nd principal component of the tassled cap transformation
MEANTCP3	LANDSAT TM 3rd principal component of the tassled cap transformation
MEANTXTME	NAIP mean texture within a 5x5 5m window
MEANTXTMI	NAIP minimum texture within a 5x5 5m window
MEANCURV	DEM derived curvature rescaled to 8 bit format
MEANCPRF	DEM derived curvature profile rescaled to 8 bit format
MEANCPLN	DEM derived curvature planform rescaled to 8 bit format
MEANELEV	DEM derived elevation in feet rescaled to 8 bit format
MEANELRR	DEM derived elevation relief ratio rescaled to 8 bit format
MEANSAEW	DEM derived slope aspect sin transformation (e-w) rescaled to 8 bit format
MEANSANS	DEM derived slope aspect cos transformation (n-s) rescaled to 8 bit format
MEANTRAD	DEM derived topographic solar radiation rescaled to 8 bit format
MEANTRRI	DEM derived terrain ruggedness index rescaled to 8 bit format

2. MODELING UNIT CONSTRUCTION

Model Areas

To make the 30 meter Landsat TM and the 1 meter NAIP data useable for image processing, both sets of data were resampled to 10 meters using a cubic convolution procedure. At 10m resolution, datasets are still quite large, and to accommodate the capabilities of current USFS computers, discrete mapping areas were created. The individual mapping areas are referred to as map models, or simply models. Another advantage of creating smaller modeling units is that different vegetation types could be modeled more effectively as all types do not occur in the same proportions in all models. Model delineations were based on the combination of sixth code watershed boundaries and the Nez Perce-Clearwater (NPC) administrative boundary. Specifically, the overall mapping boundary was established by the intersection of watershed boundaries and the NPC administrative boundary, where all watershed areas that intersected the NPC boundary were selected for mapping. This provided full coverage of the area within a reasonable distance from National Forest System (NFS) lands. The individual model areas were defined in a similar way, focusing on the interaction between Ranger District and watershed boundaries. In all, ten sub- models were created to cover the entire NPC, ranging in size from 400,000 to 800,000 acres, with an average size of roughly 690,000 acres. The largest mapping area spans the Kelly Creek watershed. Final model area boundaries are shown in Figure 1.

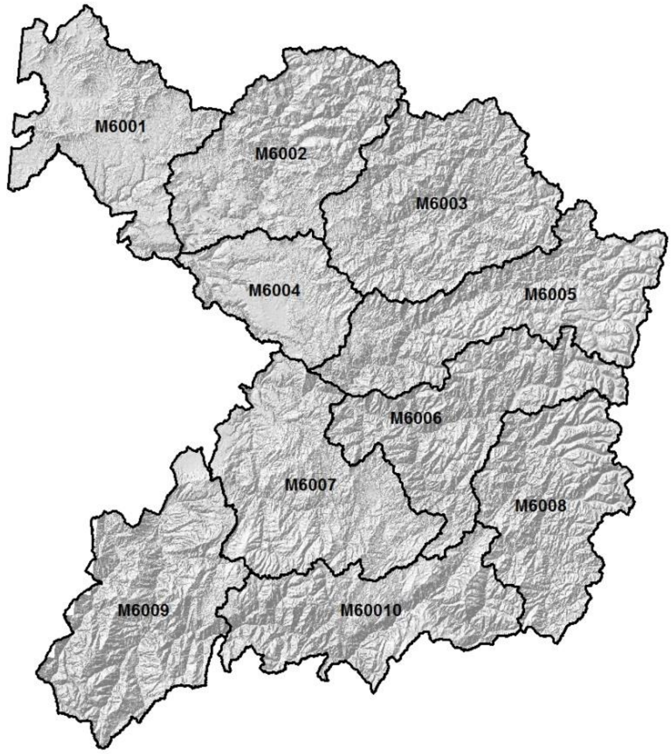


Figure 1. *Vegetation modeling units within the Nez Perce-Clearwater National Forests are labeled as M6001- M6010 and illustrated by heavy black lines.*

Image Segmentation

Image segmentation is the process of combining pixels within digital images into spatially cohesive regions. These individual regions are called image objects and represent distinct areas within the image that depict elements of vegetation and other patterns on the landscape (McDonald et al. 2002).

Image objects are inherently more data rich than individual pixels, and form the building blocks upon which image classifications are built (Haralick and Shapiro 1985, Ryerd and Woodcock 1996). Ultimately, the raster-based image objects are converted to vector-based polygons with associated image statistics as attributes. The segmentation process is performed using a proprietary software package known as eCognition, and is based on the local variance structure within imagery and user defined parameters.

The initial segmentation is completed on an individual map model basis. It is of a moderate spatial resolution, based on a defined scale parameter along with shape and spectral metrics. The segmentation is then classified into the basic VMap lifeform classes of 1) sparsely-vegetated, 2) nonforest herbaceous and shrub vegetation, 3) forest, 4) and water, using membership functions and/or nearest neighbor algorithms within the eCognition software. A classification-based segmentation is subsequently applied to each of the mapped lifeform classes. Specifically, multiple polygons that constitute a lake will be merged into a single polygon representing the lake. Likewise, many small polygons representing rocky ridges will be allowed to grow into bigger polygons because distinctions between rock types are generally not considered important to maintain in a vegetation database. Polygons representing the nonforest vegetation will generally be re-segmented into smaller polygons to capture elements of detail that are important in rangeland communities. Conversely, polygons representing forest vegetation will be re-segmented to yield larger units to allow for some variation within forest stands. Results of the classification-based segmentation yield the polygons of the NPC VMap V14 Database.

Figure 2 illustrates results of image segmentation on the NPC in sub-model M6002, displayed over 1m NAIP color infrared imagery. Distinctions between lifeform classes such as sparse vegetation, grass, water, and forest can easily be determined. Similarly, differences in forest canopy cover and reflectance are also clearly visible, and delineated by the segmentation process.

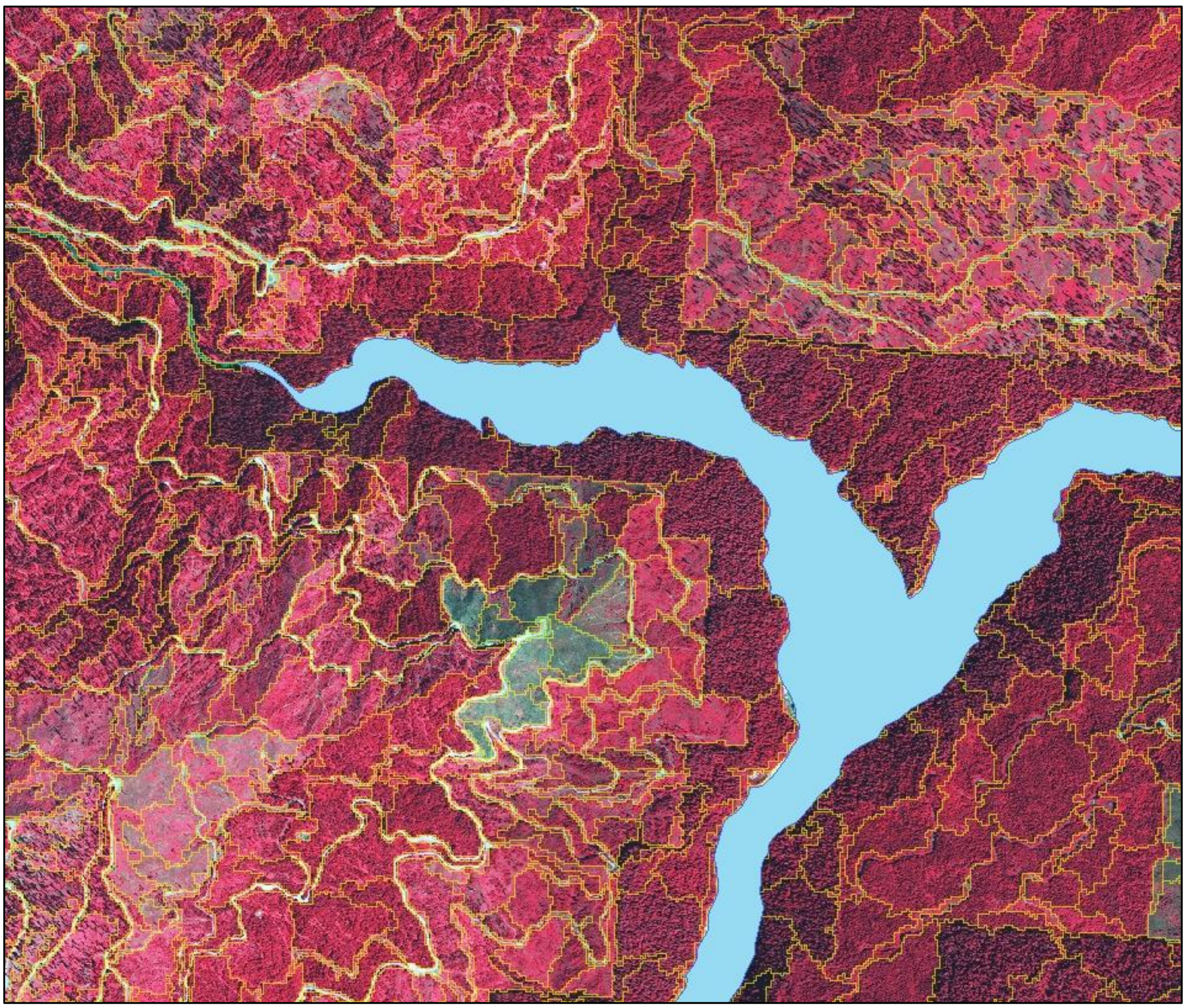


Figure 2. *Illustration of VMap V14 polygons in the Nez Perce-Clearwater National Forest*

3. TRAINING DATA

The quality of any remote sensing product is strongly related to the quality of the ground truth data associated with it. Ground or other reference data is used to build the relationships between the observed phenomena and the spectral and biophysical information derived from remotely sensed and ancillary data. Collectively, ground and other reference data are known as training data because they are used to construct algorithms that relate observations to quantified variables and are used to interpret and label previously unsampled areas within a study area. Thus, they “train” the algorithm to distinguish between, and label the unknown areas within a modeling area.

In the VMap process, image object-based polygons are the units within which training data are collected. Collection of training data is primarily ground-based sampling, and is supplemented with image interpretation when/where appropriate. For instance, data such as lifeform, dominance type, and tree canopy cover could be interpreted from the 1m NAIP if personnel are familiar with the area.

Landscape Stratification

One of the primary goals of field data collection is to capture the variability of the vegetation types that occur across the landscape. Based on previous approaches tested during the Beaverhead-Deerlodge, and Flathead National Forests VMap Database production (Brown and Ahl, 2011, Ahl and Brown 2012) it was found that a landscape stratification based sample design that accounts for variation in climatic, geologic, vegetative, and topographic characteristics can be accomplished by modeling the interaction between basic lifeform and elevation classes across a study area. Since many of the layers used to describe biophysical properties of the landscape are modeled from elevation values, the modeling process was simplified by focusing directly on elevation values as a primary component of the stratification.

To begin, data from the National Elevation Dataset (NED) originally provided continuous elevation estimates rounded to the nearest foot, but this level of detail was difficult to work with. Therefore the dataset was reclassified into three classes, essentially representing low, medium, and high elevation landscape units. The Natural Breaks classification algorithm was used to parse the elevation histogram into the three specified classes, which is shown in the example below (Figure 3).

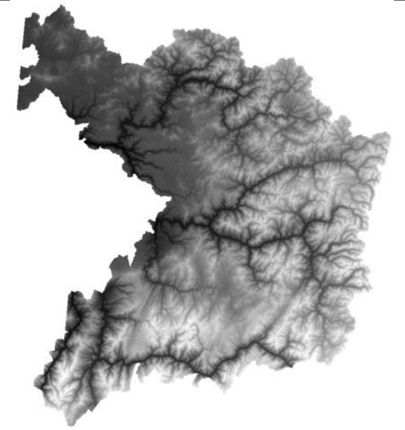
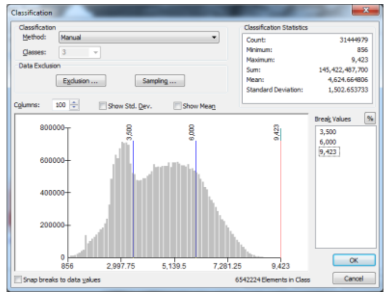
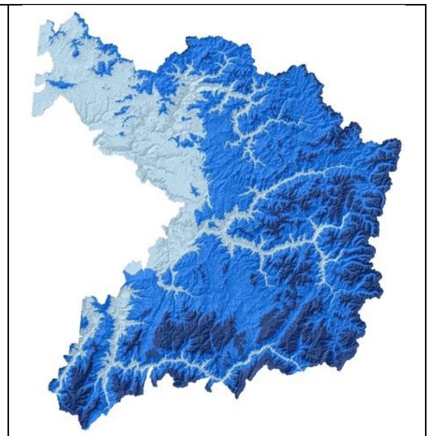
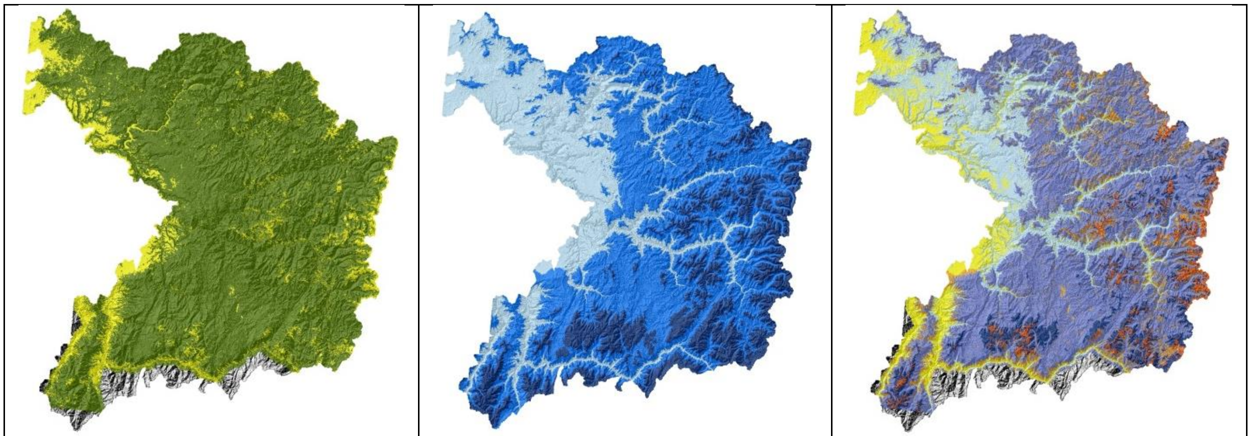
		
A) Elevation in feet	**B**) Classification Algorithm	**C**) Low, Medium, High Elevation Classes

Figure 3. C*lassification of continuous elevation data using the natural breaks algorithm to produce three classes ranging from 1) 0 – 3,500, 2) 3,501 - 6,000) and 3) greater than 6,001 ft, shown in pink, green, and blue, respectively*

Further division of the landscape focused on the distribution of vegetation. While more complex datasets were considered (i.e., mapped distributions of geomorphic land types and their various associations (R1 LTA), regional geology, and Level 4 Ecoregion data layers) a basic classification of forest versus non-forest lifeforms provided the most meaningful and straight-forward interpretation. The four basic classes of lifeform established during the segmentation process were reduced into two categories describing the basic forest and non-forest lifeforms across the NPC.

The final land unit stratification was completed by combining both the vertical and horizontal elements of the landscape. The vertical elements represented the low, moderate and high elevation classes, and the horizontal elements were composed of forest and non-forest vegetation types (Figure 4).



A) Lifeform with 2 classes	**B**) Elevation with 3 classes	**C**) ELE-LFM with 6 classes

Figure 4. *Development of the final landscape stratification dataset based on forest and non-forest lifeforms and elevation zones. Two classes of A) lifeform were combined with three classes of B) elevation to create 6 unique combinations (strata) of vertical and horizontal landscape features.*

Sampling vegetation within the unique combinations of forest and non-forest types over a range of elevation classes ensures that the spectrum of expected environmental conditions in the NPC landscape is fully captured.

Sampling within Strata

Upon development of the biophysical strata composing the NPC model areas, the next stage of the VMap sampling strategy is to identify potential sites for field review. There are three essential considerations in the development of a proposed sample network. The first priority is an appropriately proportioned sampling distribution across the landscape. Second, it is desirable to collect as many high quality samples as possible. Third, the time and effort needed to access suggested sample sites must be balanced against the need to acquire a certain number of samples during the field season because spending excessive effort to visit a few remote sample sites is not as efficient as collecting more, but easier to obtain samples.

To set up a spatially proportionate sample design, a systematic grid of points with 500 meter spacing across the entire study area was created, where each point represents a potential field review site. Each point was attributed with a vegetation model identification number, and relevant Strata code. The basic assumption is that if all potential sites are reviewed, a proportionate sample of landscape features and associated vegetation characteristics will be sampled. Given that it will not be possible to visit all sites, further stratification is necessary to derive a realistic proposed sample network that is reasonable in terms of space and time.

As a first step towards reducing the potential sample points down to a reasonable number it was assumed that the existing roads & trails network will determine the primary access to proposed sites. Realizing the amount of time required to record sample data is limited, we applied a 1 km buffer (about 0.5 mile) buffer around the road network. The zone identified by the buffered network then represents potential areas within which vegetation modeling units, constrained by

Forest Service ownership that may be visited by a sample collection crew with a reasonable amount of effort. An example of this buffer network and final samples collected is given below for the NPC model in Figure 5. This illustration shows the stratified landscape, the buffered access network, and the locations where training data were collected for NPC VMap production. Following Figure 5 is Table 2, which summarizes the type and number of data that were collected during the field season.

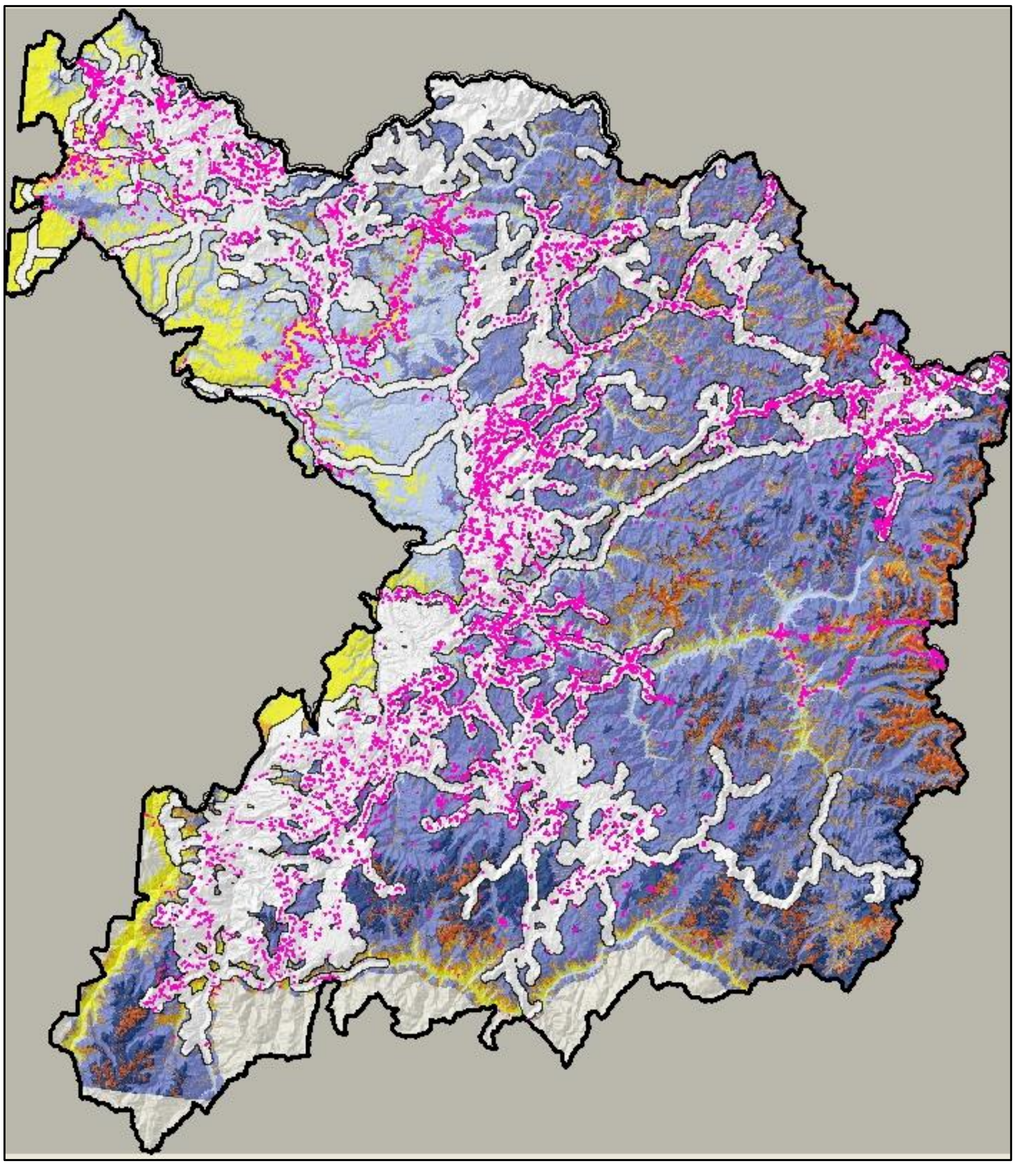


Figure 5. *NPC stratified sample design and data collection location sites*

Table 2. *Summary of samples collected for NPC VMap Version 14 production.*

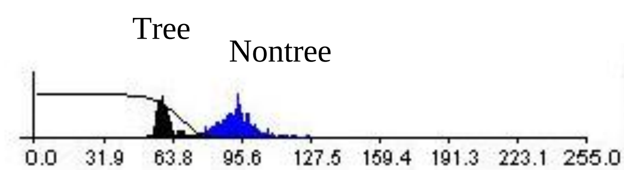
Nez Perce-Clearwater Vmap 2014 Sample Distribution				
DTB_SAMP	DTB All Quality		CCV_SAMP	CCV All Quality
8010	549		4001	547
8013	284		4002	1,047
8020	369		4003	2,521
8023	755		4004	2,870
8024	31		Total	**6,985**
8030	834			
8033	48			
8034	842		**TSZ_SAMP**	**TSZ All Quality**
8040	49		4100	568
8043	75		4200	1,097
8044	23		4300	1,966
8050	696		4400	2,118
8053	189		4500	477
8054	27		Total	**6,226**
8060	168			
8064	263			
8070	177			
8074	260		**NF_SAMP**	**NF All Quality**
8080	7		3100	520
8083	20		3320	2
8090	215		3330	385
8094	299		Total	**907**
8110	110			
8114	48			
8120	7			
8123	10			
8133	5			
8160	45			
8170	2			
8400	59			
8500	20			
8600	10			
Total	**6,496**			

4. IMAGE CLASSIFICATION

Labeling Algorithms

The Federal Geographic Data Committee (FGDC) Vegetation Classification Standards (FGDC 1997) establishes a hierarchy of existing vegetation classification with nine levels of definition. The top seven levels are primarily based on physiognomy. The two lower levels refer to vegetation alliance and association, and are based on floristic attributes. The USDA Forest Service has set the national direction for classification and mapping of existing vegetation to implement the FGDC standards, and to provide direction for classifying and mapping structural characteristics (Brohman and Bryant 2005). This direction applies to a variety of geographic extents and thematic resolutions characterized as map scale levels. The Northern Region Vegetation Mapping Program (VMap), and resulting existing vegetation database, is specifically designed to meet this national program direction at the mid-level.

Attributing of VMap products is accomplished using a multi-step process. The image classification process begins with the segmentation procedure. Image-objects created during the segmentation routine are first labeled according to lifeform classes using algorithms within the eCognition software. This tool uses an hierarchical classification scheme, and for features that are fairly easy to discern from image statistics, such as 1) tree, 2) nonforest vegetation, 3) water, and 4) sparse vegetation, membership functions were used to properly label these cover types. Figure 6 is an example of how one of these functions is implemented in the software interface.



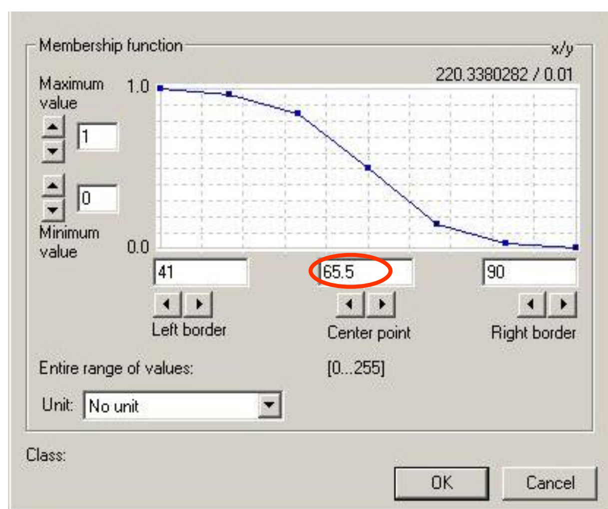


Figure 6. *Illustration of an eCognition membership function, where 'tree' samples are in the blue histogram, and 'nontree' sample data are represented by the black histogram for one of the image inputs. The histogram is used to create a membership function that excludes 'tree' at 65.5 for this input. A series of functions can be created for all image inputs that show separation and combined to create classified outputs.*

Following segmentation and initial lifeform classification, a polygon layer with associated image and biophysical input statistics from each model area is exported. This data is then associated with the field collected training data and further analyzed with a data mining algorithm known as Random Forests (Breiman and Cutler, 2008). The algorithm is used with a custom built user interface to derive tree dominance type, tree canopy cover, and tree size classifications within the tree lifeform. Using a similar approach, grass and shrub types were defined from within the initially determined non-forest lifeform.

Tree canopy cover is defined as “cover from above”. This metric describes how much live canopy is present to intercept light/precipitation prior to its reaching the forest floor. This is measured as a percent and then divided into 4 classes: Low (10-25% cover), Moderate-Low (25-40% cover), Moderate-High (40-60% cover), and High (60%+ cover).

Tree size is mapped into four classes based on a canopy cover weighted average DBH. The classes are: Seedling/Sapling (0-5” DBH), Small (5-10” DBH), Medium (10-15” DBH), and Large (15-20” DBH) and Very Large (20”+ DBH).

Tree dominance is mapped as two different, but related, classifications based on a basal area weighted plurality; Dominance of 40% (DOM40) and Dominance of 60% (DOM60). For more details about VMap dominance type, tree size, and tree canopy cover classes please refer to the *Region 1 Multi-level Classification, Mapping, Inventory, and Analysis System* (Berglund and others, 2009).

Implementation of this classification approach yields five primary attributes that populate the polygon features of the database, consisting of lifeform, dominance type 40 and 60, tree canopy cover, and tree size class.

5. MAP PRODUCT REVIEW

Updating for Disturbance

There were quite a few fires that burned across the NPC in the time since image acquisition until product delivery. In an attempt to help quantify this large disturbance within the database a remote sensing based fire severity estimate was conducted using pre- and post-fire Landsat imagery per the standards utilized by the Monitoring Trends in Burn Severity Program (www.mtbs.gov).

Fire disturbed polygons were identified through a zonal majority function conducted between the database and the burn severity raster. Each polygon with a majority burn severity class of Moderate-High or higher was labeled as "Transitional Forest" within the VMap database. Any other lesser disturbance class was left with the original map class label.

Map Product Review and Assessment

As part of the review process, all mapping areas were visited during the field data collection process in the summer of 2012. While these data were used to parameterize the classification algorithm, the field observations of the analysts were further used to refine results of the automated classification process (Brown, 2012).

After the review process a map accuracy assessment was conducted. Results of the assessment are presented separately in Numbered Report NRGG 15-01 (Brown, 2014). This report explains accuracy assessment concepts and describes results of the NPC VMap V14 Database.

6. ENHANCED DATA

In addition to the standard VMap database, a suite of additional products were created for the NPC. The first of those additional products was a summary of FIA-based attributes for each unique combination of forest dominance type, canopy cover, and size class attributes. Additionally, individual dominace type (DOM40) classification probability surfaces were generated for all relevant dominace types occurring within NPC.

Individual Dominance Type Probability Surfaces

Continuous surfaces of VMap dominance types were created for the NPC using the full suite of forest-based training data collected between 2012 and 2014. The likelihood of occurrence of each dominance type was modeled based on the distribution of said type's training data versus the training data from all other types.

For instance, to estimate the likely distribution of ponderosa pine across the landscape, training data representing this particular type were classified against training data from all other types combined. As such, a classification of ponderosa pine samples was placed in contrast to all samples of all other types combined to yield a continuous surface that represents the likelihood of being classified as ponderosa pine versus not being classified as ponderosa pine. Pictured in the following figures are representations of the individual dominance type distributions across the NPC landscape where the darkest shade of red suggests the highest likelihood of dominance for the specified type. As red fades towards orange, yellow, green and blue, the estimated likelihood of dominance decreases.

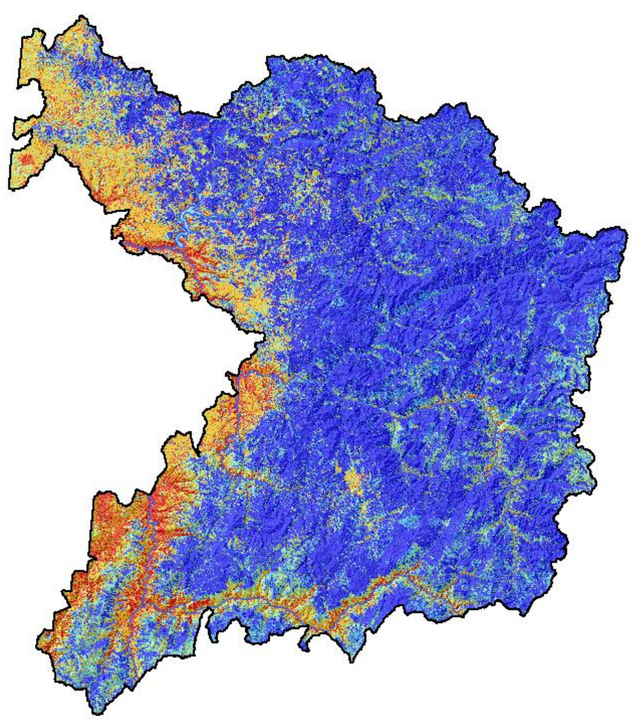


Figure 7. *Ponderosa pine, VMap DOM_MID_40 code = 8015*

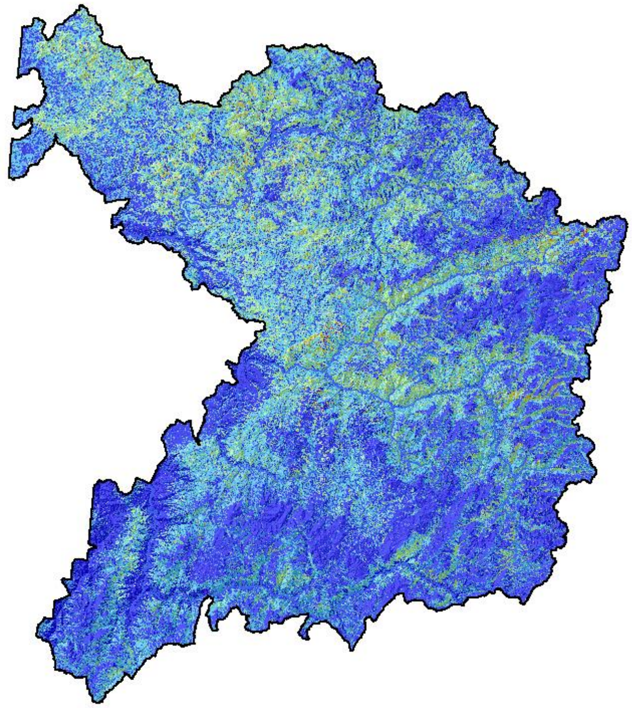


Figure 8. *Douglas-fir, VMap DOM_MID_40 code = 8025*

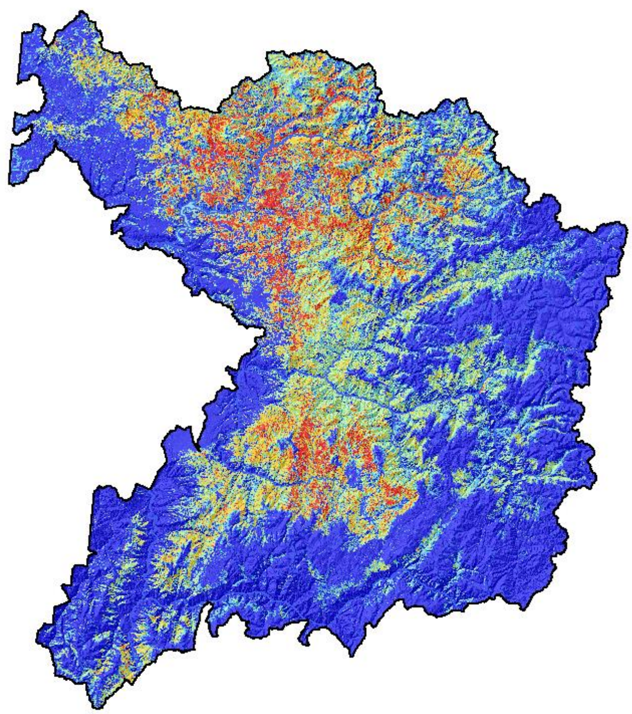


Figure 9. *Grand fir, VMap DOM_MID_40 code = 8035*

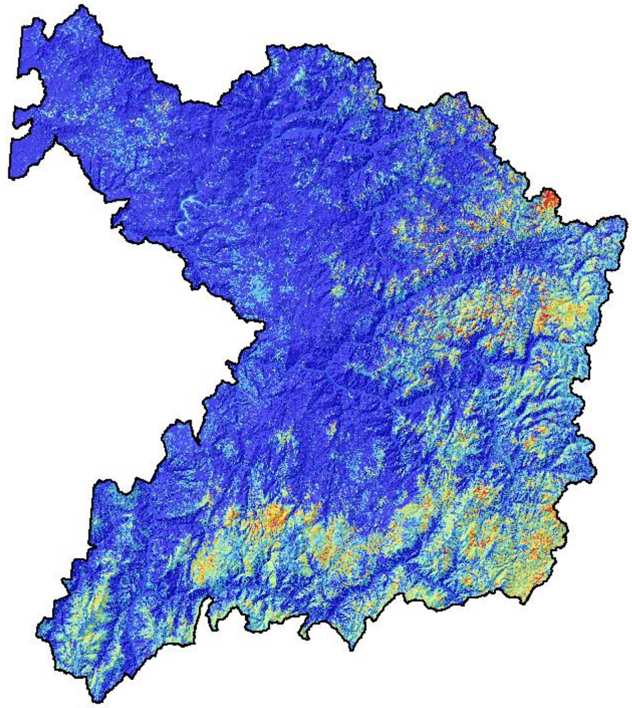


Figure 10. *Lodgepone pine, VMap DOM_MID_40 code = 8055*

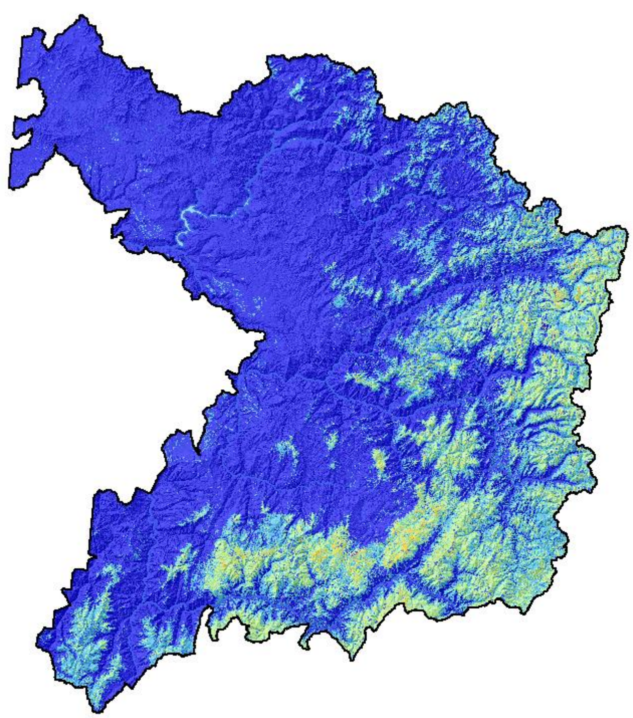


Figure 11. *Subalpine fir, VMap DOM_MID_40 code = 8065*

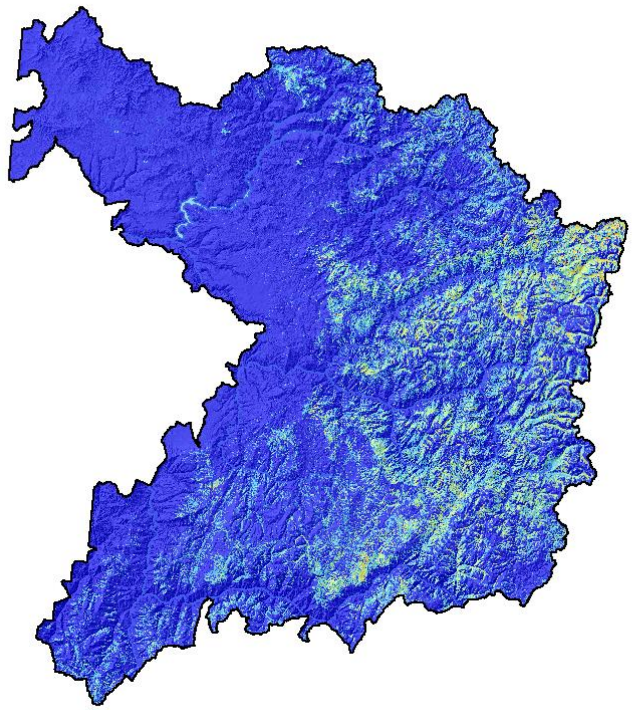


Figure 12. *Engelmann spruce, VMap DOM_MID_40 code = 8075*

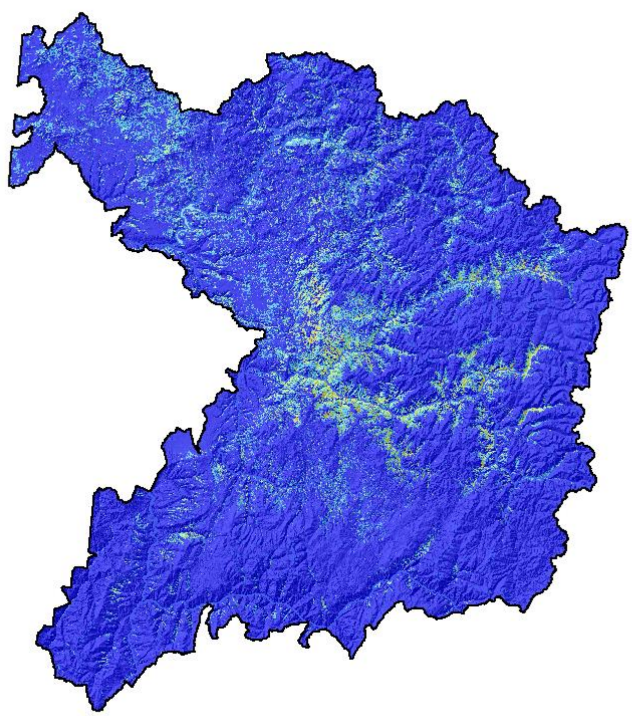


Figure 13. *Western redcedar, VMap DOM_MID_40 code = 8095*

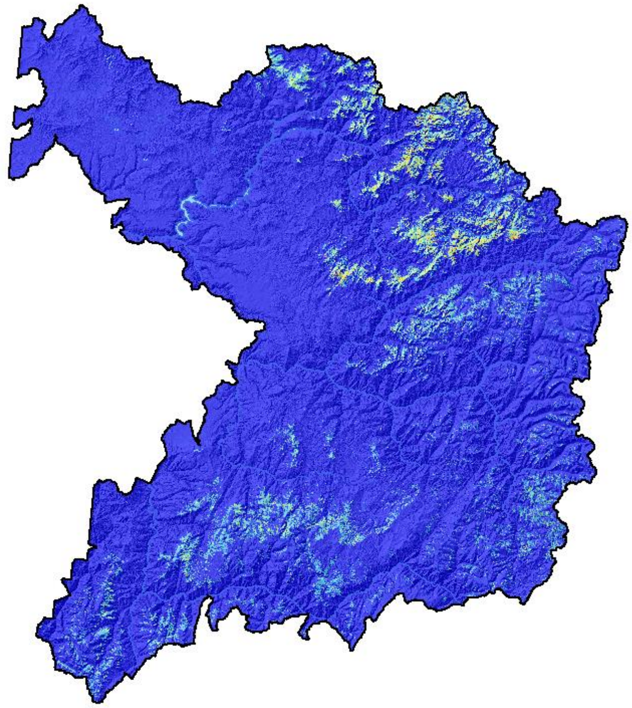


Figure 14. *Hemlock SPP, VMap DOM_MID_40 code = 8115*

7. LITERATURE CITED

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